NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

REALTIME CLASSIFICATION OF ECG WAVEFORMS FOR DIAGNOSIS OF DISEASES

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REALTIME CLASSIFICATION OF ELECTROCARDIOGRAM WAVEFORMS FOR DIAGNOSIS OF DISEASES

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF

Bachelor of Technology
In
Electrical Engineering

By
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&
K. Goutham

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Department Of Electrical
Engineering
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ROURKELA

CERTIFICATE

This is to certify that the thesis entitled, *"real-time classification of ECG signals for diagnosis of diseases"* by Soumya Ranjan Mishra and K Goutham in partial requirements for the curriculum requirement of Bachelor of technology in Electrical Engineering at National Institute Of Technology, Rourkela, is an authentic work carried out by them under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree.

Date:

Dr. Dipti Patra
Electrical Engineering
NIT, Rourkela

CONTENTS

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We would like to thank the faculty of Electrical Engineering department of NIT, Rourkela for being the panacea to all our queries.

Last but not the least, we would like to thank all our dear friends for being their wikipediaic knowledge and unrelenting support.

Regards,

Soumya Ranjan Mishra

K Goutham

ABSTRACT

Signal Processing is undoubtedly the best real time implementation of a specific problem. Wavelet Transform is a very powerful technique for feature extraction and can be used along with neural network structures to build computationally efficient models for diagnosis of Biosignals (ECG in this case). This work utilises the above techniques for diagnosis of an ECG signal by determining its nature as well as exploring the possibility for real-time implementation of the above model. Daubechies wavelet transform and multi-layered perceptron are the computational techniques used for the realisation of the above model. The ECG signals were obtained from the MIT-BIH arrhythmia database and are used for the identification of four different types of arrythmias. The identification was implemented real-time in SIMULINK, to simulate the detection model under test condition and verify its workability.

INTRODUCTION

Electrocardiography deals with the electrical activity of the heart. Monitored by placing sensors at limb extremities of the subject, the electrocardiogram (ECG) is a record of the origin and propagation of electrical potential through cardiac muscles. It is considered a representative signal of cardiac physiology, useful in diagnosing cardiac disorders. [Acharya, Dua, Bhat, Iyengar, Roo,2002];[Owoski and Linh, 2001]; [Ceylan and Ozbay, 2007].

The medical state of the heart is determined by the shape of the Electrocardiogram, which contains important pointers to different types of diseases afflicting the heart. However, the electrocardiogram signals are irregular in nature and occur randomly at different time intervals during a day. Thus arises the need for continuous monitoring of the ECG signals, which by nature are complex to comprehend and hence there is a possibility of the analyst missing vital information which can be crucial in determining the nature of the disease. Thus computer based automated analysis is recommended for early and accurate diagnosis. [Acharya, Roo, Dua, Iyengar, Bhat, 2002]

The biggest challenge faced by the models for automatic heart beat classification is the variability of the ECG waveforms from one patient to another even within the same person. However, different types of arrhythmias have certain characteristics which are common among all the patients. Thus the objective of a heart beat classifier is to identify those characteristics so that the diagnosis can be general and as reliable as possible. One of such methods which can be reliably used for ECG classification is the use of neural networks. Neural networks are one of the most efficient pattern recognition tools because of their high nonlinear structure and tendency to minimise error in test inputs by adapting itself to the input output pattern and thus establishing a nonlinear relationship between the input and output.

However the performance of a neural network is highly dependent on the number of input elements in the computational layers.

A large number of elements would lead to a large number of multiplication and additions and the network would become expensive on computing resources.

Thus to reduce the number of inputs a pre-processing layer is used. This pre-processor uses wavelet transform to "smooth" out the ECG waveforms and reduce the number of samples while preserving all the distinct signal features such as local maxima and minima. Also the use of wavelet transform makes the model to be implemented easily in real time processing by the use of FIR filters.

The model so obtained was implemented in a real-time model which was simulated with Simulink software package. The basic processing strategy is shown below. Each bock represents a processing milestone. The first block is the pre-processor which was described previously and the second block is the neural network block which does the actual processing.

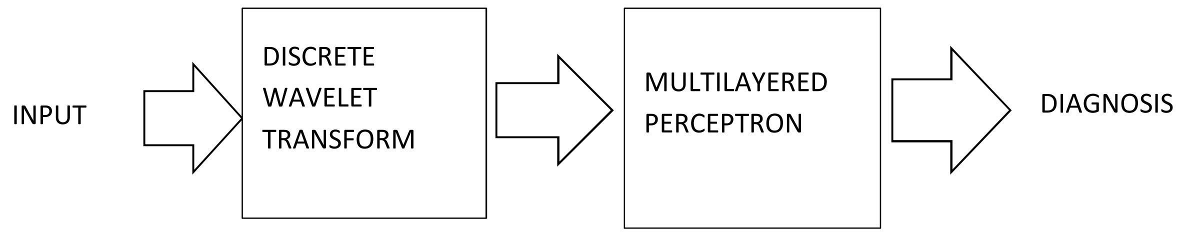


Fig. 1.1 general processing architecture

BACKGROUND

1. The Electrocardiogram:

Electrocardiography (ECG) is a transthoracic interpretation of the electrical activity of the heart over time captured and externally recorded by skin electrodes. [ECG simplified by Ashwin Kumar]. The ECG works by detecting and amplifying the tiny electrical changes on the skin that are caused when the heart muscle "depolarises" during each heartbeat. At rest, each heart muscle cell has a charge across its outer wall, or cell membrane. Reducing this charge towards zero is called de-polarisation, which activates the mechanisms in the cell that cause it to contract. During each heartbeat a healthy heart will have an orderly progression of a wave of depolarisation that is triggered by the cells in the sinoatrial node, spreads out through the atrium, passes through "intrinsic conduction pathways" and then spreads all over the ventricles. This is detected as tiny rises and falls in the voltage between two electrodes placed either side of the heart which is displayed as a wavy line either on a screen or on paper. This display indicates the overall rhythm of the heart and weaknesses in different parts of the heart muscle.

Usually more than 2 electrodes are used and they can be combined into a number of pairs. (For example: Left arm (LA), right arm (RA) and left leg (LL) electrodes form the pairs: LA+RA, LA+LL, RA+LL) The output from each pair is known as a lead. Each lead is said to look at the heart from a different angle. Different types of ECGs can be referred to by the number of leads that are recorded, for example 3-lead, 5-lead or 12-lead ECGs (sometimes simply "a 12-lead"). A 12-lead ECG is one in which 12 different electrical signals are recorded at approximately the same time and will often be used as a one-off recording of an ECG, typically printed out as a paper copy. 3- and 5-lead ECGs tend to be monitored continuously and viewed only on the screen of an appropriate monitoring device, for example during an operation or whilst being transported in an ambulance. There may, or may not be any permanent record of a 3- or 5-lead ECG depending on the equipment used.

The ECG waveform is shown in the figure 2.1here. The ECG waveform can be broken down into three important parts each denoting a peak on the either side represented by P, Q, R, S, T. each of them represent a vital processes in the heart and those processes have been illustrated in table 2.1. In case of a disease afflicting the heart, the waves get distorted according to the area which is not functioning normally. Thus by inspection of the ECG waveform the nature of disease can be found out easily.

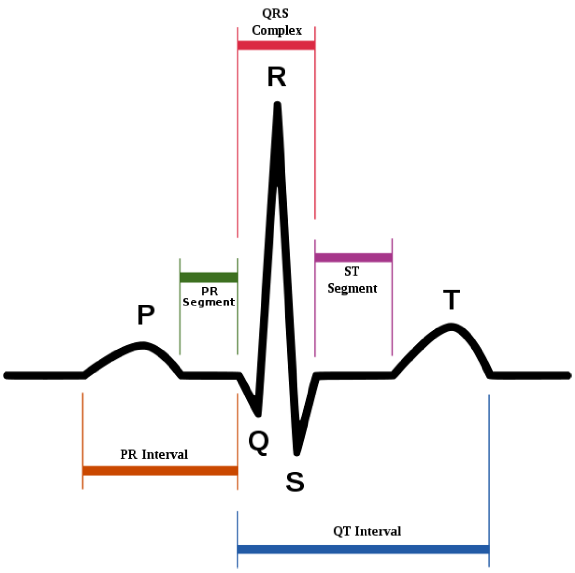


TABLE 2.1

Feature	Description	Duration
RR interval	The interval between an R wave and the next R wave is the inverse of the heart rate. Normal resting heart rate is between 50 and 100 bpm	0.6 to 1.2s
P wave	During normal atrial depolarization, the main electrical vector is directed from the SA node towards the AV node, and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG.	80ms
PR interval	The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. The PR interval reflects the time the electrical impulse takes to travel from the sinus node through the AV node and entering the ventricles. The PR interval is therefore a good estimate of AV node function.	120 to 200ms
PR segment	The PR segment connects the P wave and the QRS complex. This coincides with the electrical conduction from the AV node to the bundle of His to the bundle branches and then to the Purkinje Fibers. This electrical activity does not produce a contraction directly and is merely traveling down towards the ventricles and this shows up flat on the ECG. The PR interval is more clinically relevant.	50 to 120ms
QRS complex	The QRS complex reflects the rapid depolarization of the right and left ventricles. They have a large muscle mass compared to the atria and so the QRS complex usually has a much larger amplitude than the P-wave.	80 to 120ms
J-point	The point at which the QRS complex finishes and the ST segment begins. Used to measure the degree of ST elevation or depression present.	N/A

Feature	Description	Duration
ST segment	The ST segment connects the QRS complex and the T wave. The ST segment represents the period when the ventricles are depolarized. It is isoelectric.	80 to 120ms
T wave	The T wave represents the repolarization (or recovery) of the ventricles. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the *absolute refractory period*. The last half of the T wave is referred to as the *relative refractory period* (or vulnerable period).	160ms
ST interval	The ST interval is measured from the J point to the end of the T wave.	320ms
QT interval	The QT interval is measured from the beginning of the QRS complex to the end of the T wave. A prolonged QT interval is a risk factor for ventricular tachyarrhythmia and sudden death. It varies with heart rate and for clinical relevance requires a correction for this, giving the QTc.	300 to 430ms
U wave	The U wave is not always seen. It is typically low amplitude, and, by definition, follows the T wave.	

Table 2.1: the description and duration of each wave in the ECG waveform

MATERIAL AND METHODS

For efficient recognition and less computationally expensive method of pattern recognition the multi-layered perceptron based neural network is used here along with wavelet compression of the input signal.

The preclassification task is performed by performing wavelet compression which reduces the number of samples by a factor of 4.The multi-layered perceptron based neural network is sued for further processing and final pattern classification.

The input data is clustered as a result of training of the neural network. In the end a SIMULINK model was developed and it implemented all the result obtained in the offline analysis. SIMULINK model helped in developing a scheme for real time implementation of the above process.

The Wavelet Transform

Frequency spectrum analysis is one of the best methods for analysis of a signal. However Fourier analysis of the signal can decompose the signal into sinusoidal entities and the filters implementing it remove certain frequencies from the spectrum. However, this might not be useful in preserving the peaks(local maxima and minima) of the signal and may lead to loss of important data pointers which are crucial to diagnosis of the condition.

However, if wavelet transform based data compression is used the peaks (as well as gaps, though they are not important in this case) can be preserved. This will preserve the important pointer and structures in the signal. The wavelet transform can be seen as an extension to the Fourier transform save it works on a multiscale basis unlike Fourier transform which works on a single domain(frequency domain).The multiscale structure of the wavelet transform decomposes the signal into a number of scales, each scale representing a particular coarseness under study.[Ceylan and Ozbay ,2007].

The process of wavelet transform is shown. After extensive experimentation on different types of wavelets the Daubechies wavelet of order 2 is used for the purpose of pre-processing of the signal as it produced the best "Smoothing" effect and preserved important local maxima and minima. The wavelet coefficients were computed using MATLAB software package. The structure of the wavelet transform is given in figure 3.1.

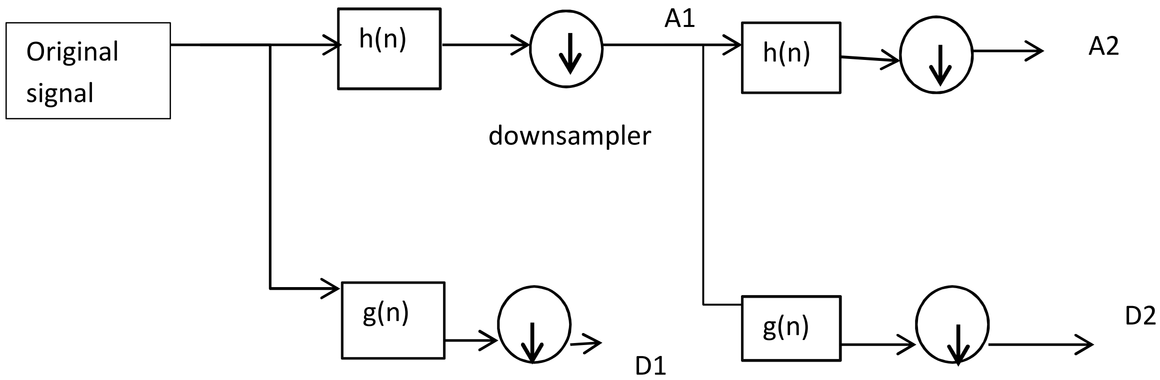


Fig 3.1. wavelet decomposition structure

The Daubechies wavelet transform

Named after Ingrid Daubechies, the Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (also called father wavelet) which generates an orthogonal multi resolution analysis.

Daubechies wavelets are chosen to have the highest number A of vanishing moments, for given support width N=2A, and among the 2A−1 possible solutions the one is chosen whose scaling filter has external phase. Both the scaling sequence and the wavelet sequence will here be normalized to have summed equal 2 and sum of squares equal 2. In some applications, they are normalised to have sum$\sqrt{2}$, so that both sequences and all shifts of them by an even number of coefficients are orthonormal to each other.

Using the general representation for a scaling sequence of an orthogonal discrete wavelet transform with approximation order *A*,

$$a(Z) = 2^{1-A}(1+Z)^A p(Z),$$

with $N=2A$, p having real coefficients, $p(1) = 1$ and $degree(p) = A-1$, one can write the orthogonality condition as

$$a(Z)a(Z) + a(Z^{-1})a(-Z^{-1}) = 4$$

OR

$$(2-X)^A P(X) + X^A P(2-X) = 2^A \ , \qquad \text{.....(1)}$$

with the Laurent-polynomial $X = \frac{1}{2}(2 - Z - Z^{-1})$ generating all symmetric sequences and $X(-Z) = 2 - X(Z)$. Further, $P(X)$ stands for the symmetric Laurent-polynomial $P(X(Z)) = p(Z)p(Z^{-1})$.

Since $X(e^{iw}) = 1 - cos(w)$ and $p(e^{iw})p(e^{-iw}) = |p(e^{iw})|^2$, P takes nonnegative values on the segment [0,2]. Equation (1) has one minimal solution for each A, which can be obtained by division in the ring of truncated power series in X,.

$$P_a(X) = \sum_{k=0}^{A-1} \binom{A+k-1}{A-1} 2^{-k} X^{-k}$$

Obviously, this has positive values on (0,2)

The homogeneous equation for (1) is antisymmetric about $X=1$ and has thus the general solution $X^A(X-1)R((X-1)^2)$, with R some polynomial with real coefficients. That the sum

$$P(X) = P_A(X) + X^A(X-1)R((X-1)^2)$$

shall be nonnegative on the interval [0,2] translates into a set of linear restrictions on the coefficients of R. The values of P on the interval [0,2] are bounded by some quantity 4^{A-r}, maximizing r results in a linear program with infinitely many inequality conditions.

To solve $P(X(Z)) = p(Z)p(Z^{-1})$ for p one uses a technique called spectral factorization resp. Fejer-Riesz-algorithm. The polynomial $P(X)$ splits into linear factors

$$P(X) = (X - \mu_1) \dots (X - \mu_N), \qquad \text{where} \quad N = A + 1 + 2\deg(R).$$

Each linear factor represents a Laurent-polynomial

$$X(Z) - \mu = -\frac{1}{2}Z + 1 - \mu - \frac{1}{2}Z^{-1}$$

that can be factored into two linear factors. One can assign either one of the two linear factors to $p(Z)$, thus one obtains 2^N possible solutions. For external phase one chooses the one that has all complex roots of $p(Z)$ inside or on the unit circle and is thus real.

Different orders of Daubechies wavelet transforms are shown below

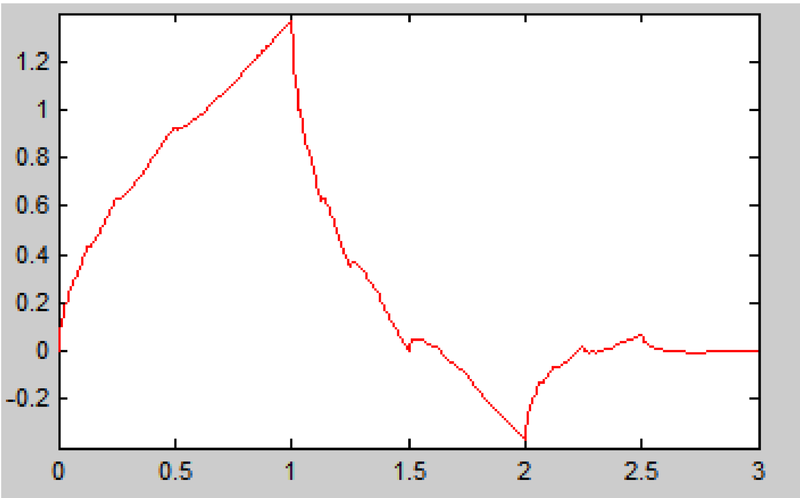


Fig 3.2:Daubechies wavelet of order 2

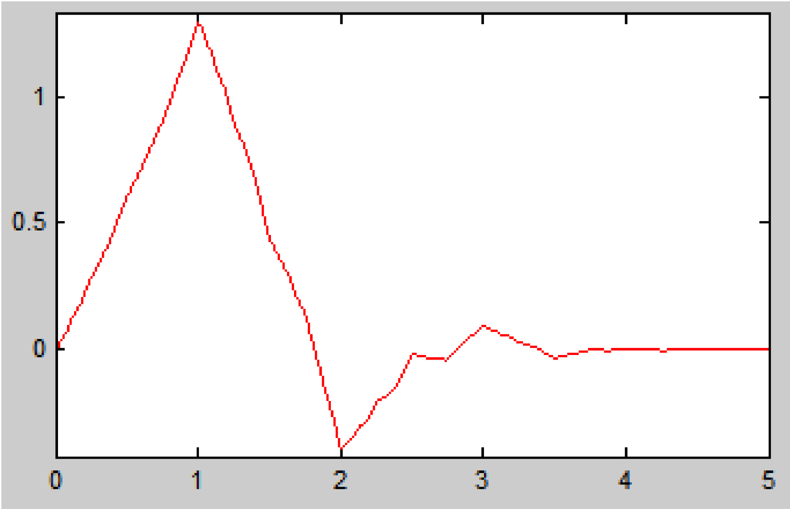


Fig 3.3:Daubechies wavelet of order 3

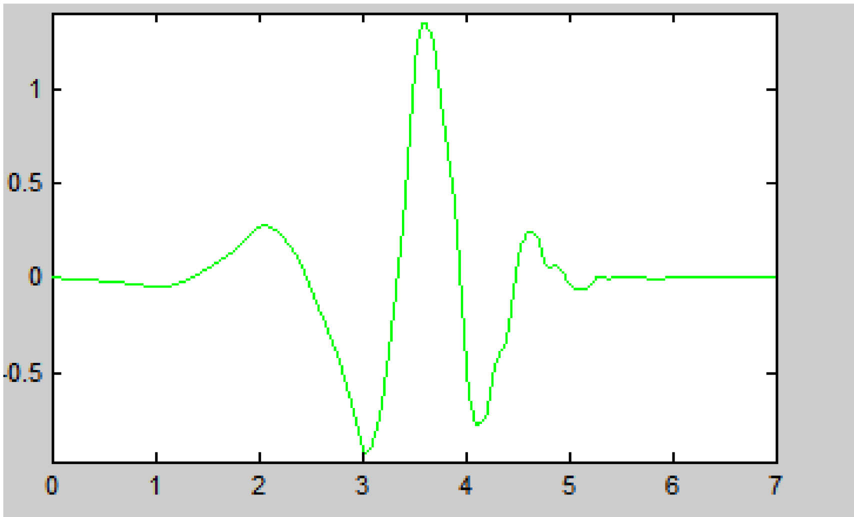


Fig 3.4:Daubechies wavelet of order 4

Multilayered Perceptron based Neural Network

Neural Networks today are synonymous with pattern recognition. The parallel processing and non-linear architecture make them ideal for finding relationship between the input and output through various adaptive algorithms. The type of neural network model used here is Multilayer Perceptron based. There are three layers namely the input, output and the hidden layer having 52, 3 and 10 elements respectively. Each element in the hidden and the output layer is fully connected to the elements in the input and hidden layer respectively.

Back propagation algorithm utilises the Levenberg-Marquardt algorithm for training of the network. It is a quasi-Newton method and is designed to approach the second order training speed without having to compute the Hessian matrix. When the performing function has a form of squares (as in typical feed forward networks).The Hessian matrix can be approximated as $\mathrm{H} = \mathrm{J}^{\mathrm{T}}\mathrm{J}$ and gradient computed as $\mathrm{G} = \mathrm{J}^{\mathrm{T}}e$. J is Jacobian matrix containing first derivatives of network errors with respect to weights and biases. Levenberg-Marquardt algorithm uses the following learning rule.

$$w_{k+1} = w_k - [J^T J + \mu I]^{-1} J^T e$$

Where μ is the gradient descent.

The main advantage of the Levenberg-Marquardt algorithm is the very fast training. For instance, in this work during the offline analysis the network was seen to train within 70 epochs. However the algorithm is very resource expensive and uses a large amount of memory. To reduce the memory usage, a modification is made to the algorithm by modifying the generation of the Hessian matrix performed by the formula given below.

$$H = J^T J = [J_1^T \ J_2^T] \begin{bmatrix} J_1 \\ J_2 \end{bmatrix} = J_1^T J_1 + J_2^T J_2$$

This reduces the memory usage significantly though the training time is increased. This is used only when the memory availability is less as in small low cost circuits.

The structure of the multi-layered perceptron network is shown below.

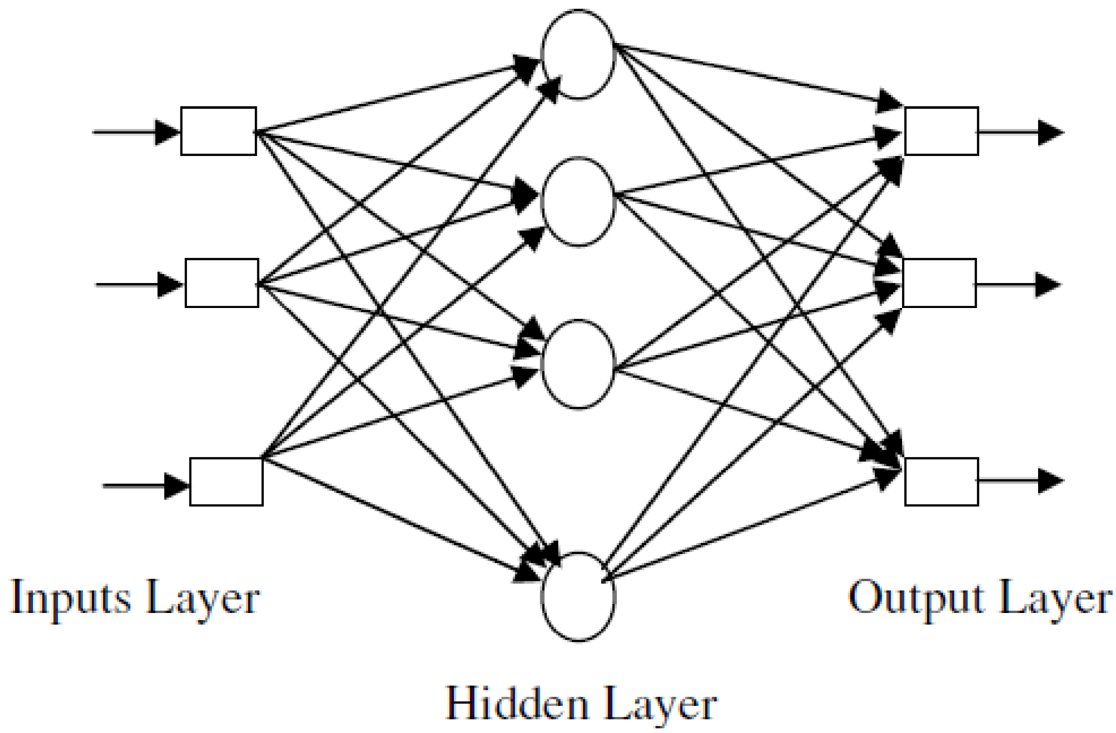


fig 3.5 Multilayered perceptron based neural network

RESULTS AND INFERENCE

1. Wavelet decomposition

The objective of this analysis was to determine the wavelet that produces result that is the closest to the original signal. Different types of wavelet analysis are shown below.

a. Daubechies decomposition of order 1 (Same as Harr wavelet decomposition):

The stages of wavelet decomposition using Daubechies wavelet of order 1 is as follows the transform was performed on the first 250 samples

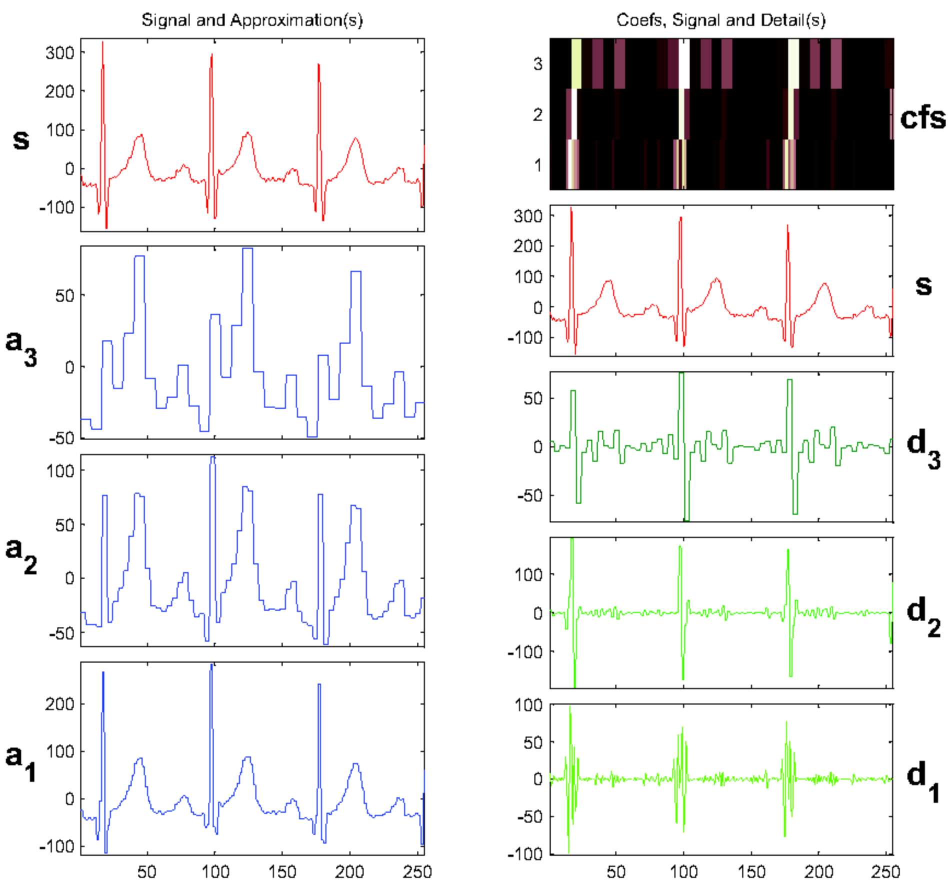


Fig 4.1 wavelet decomposition using Daubechies wavelet of order 1

Inference: this wavelet decomposition provides a step output and on higher levels of decomposition, the signal loses its identity, as the peaks are lost. Thus, this signal is unfit for use in neural networks.

b. **Daubechies wavelet of order 2:** As in the former case, this wavelet decomposition also considers first 250 samples and the results from decomposition are shown below.

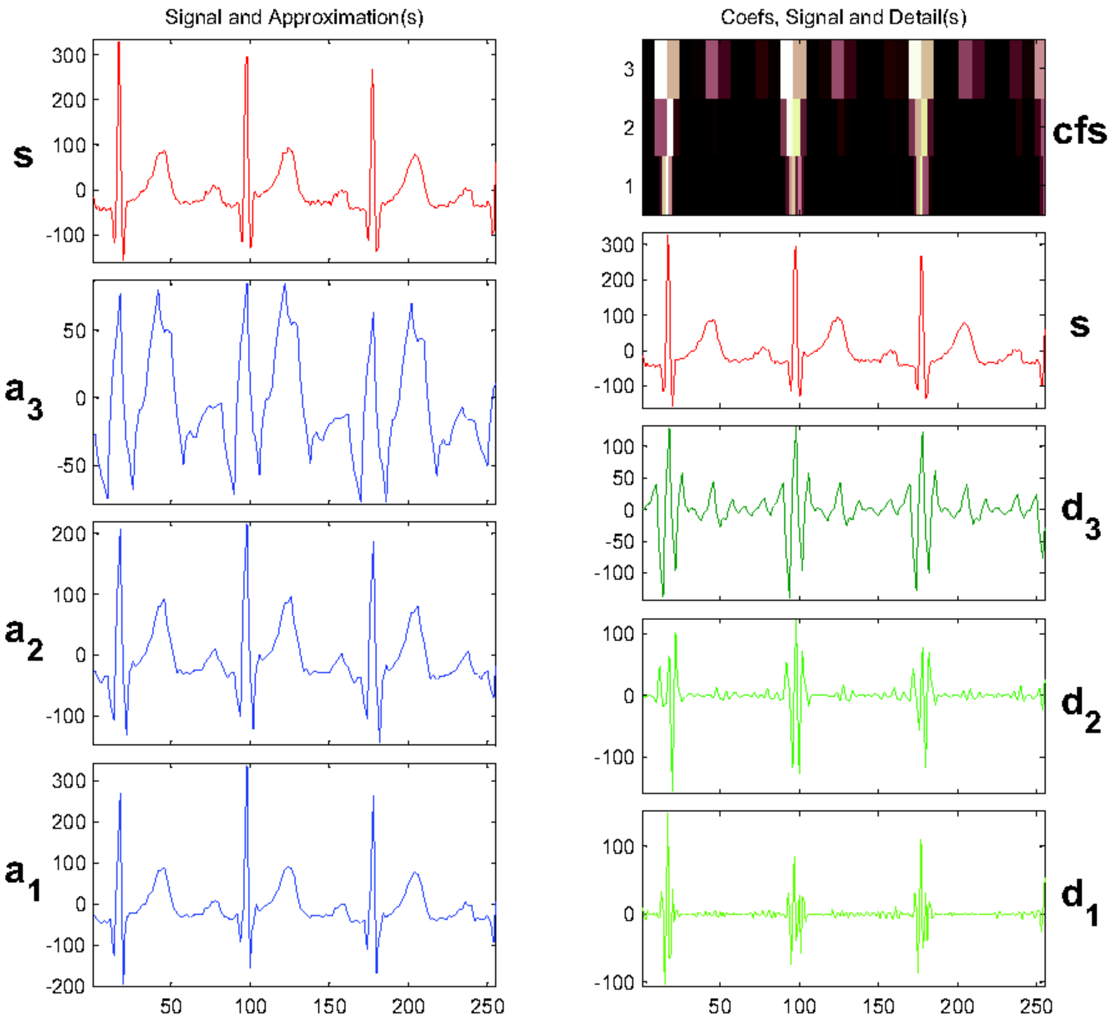


Fig 4.2 : wavelet decomposition of second order up to level 3

Inference: The result obtained here can be seen to be smoothed until the second level of the wavelet transform. After the second level of transform, the signal becomes distorted.

Two level wavelet transform is more apt for processing as the best smoothing can be achieved with 2 levels without sacrificing accuracy. The number of samples is reduced to one-fourth of the initial number of samples.

C. **Daubechies wavelet decomposition of order 3:** As in the former case, this wavelet decomposition also takes first 250 samples into account and the results from decomposition are shown below.

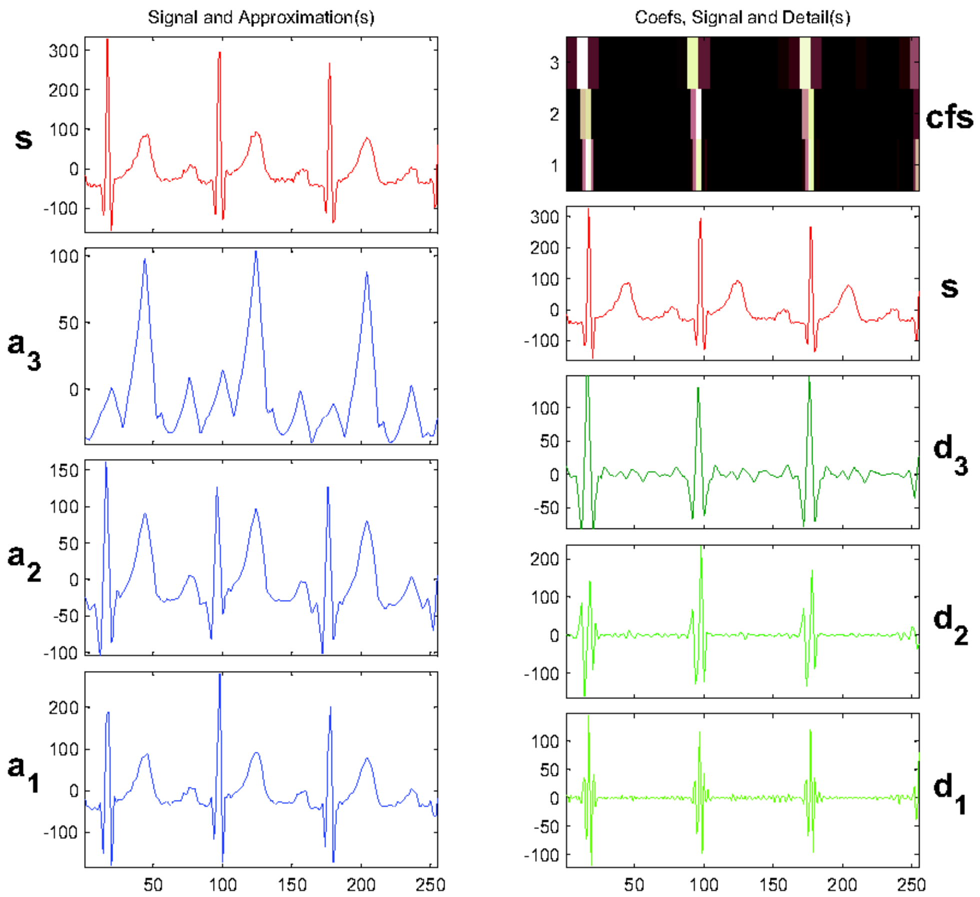


Fig 4.1 wavelet decomposition using Daubechies wavelet of order 1

Inference: this decomposition leads to a large deviation from original hence not recommended for further processing.

Note: Higher order wavelet decomposition produces more deviation and was not taken into account for further processing. Thus, the second order Daubechies wavelet transform was used for further processing in the neural network.

2. Neural network analysis:

The samples, obtained after preprocessing in the preprocessor, which utilizes wavelet transform to reduce the number of samples to one-fourth of the original, were fed to the neural network for final processing. The neural network was trained to obtain the final weights and biases. The performance parameters during training of the network are shown below.

a. **Training performance:** given by variation of mean square error with number of epochs. The following graph is obtained.

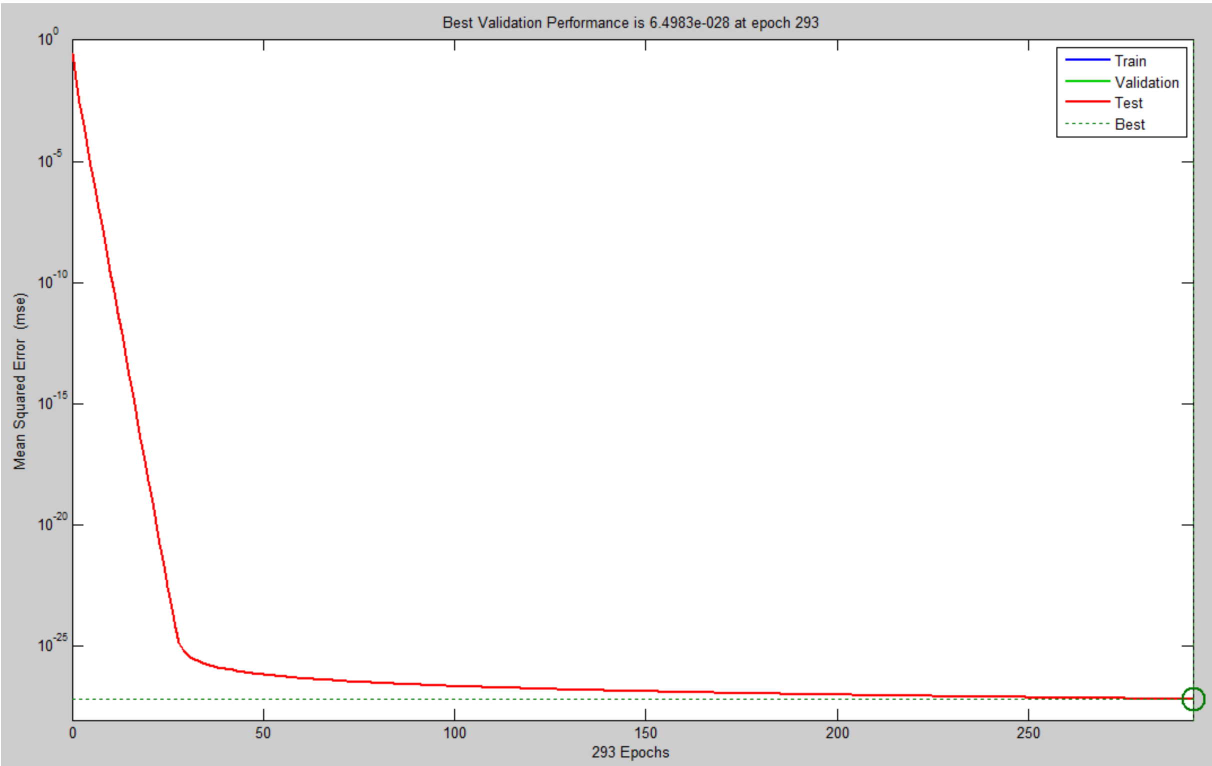


Fig 4.4 :neural network training performance

It can be observed that the mean square error decreases rapidly till epoch 30 and after that decreases slowly. A total number of 293 epochs are shown in the in the above figure. The rapid decrease in the mean square error can be attributed to the use of the Levenberg-Marquardt algorithm for training of the neural network.

b. **Other performance parameters and training state:** the following training state parameters are also obtained during the Neural Network analysis.

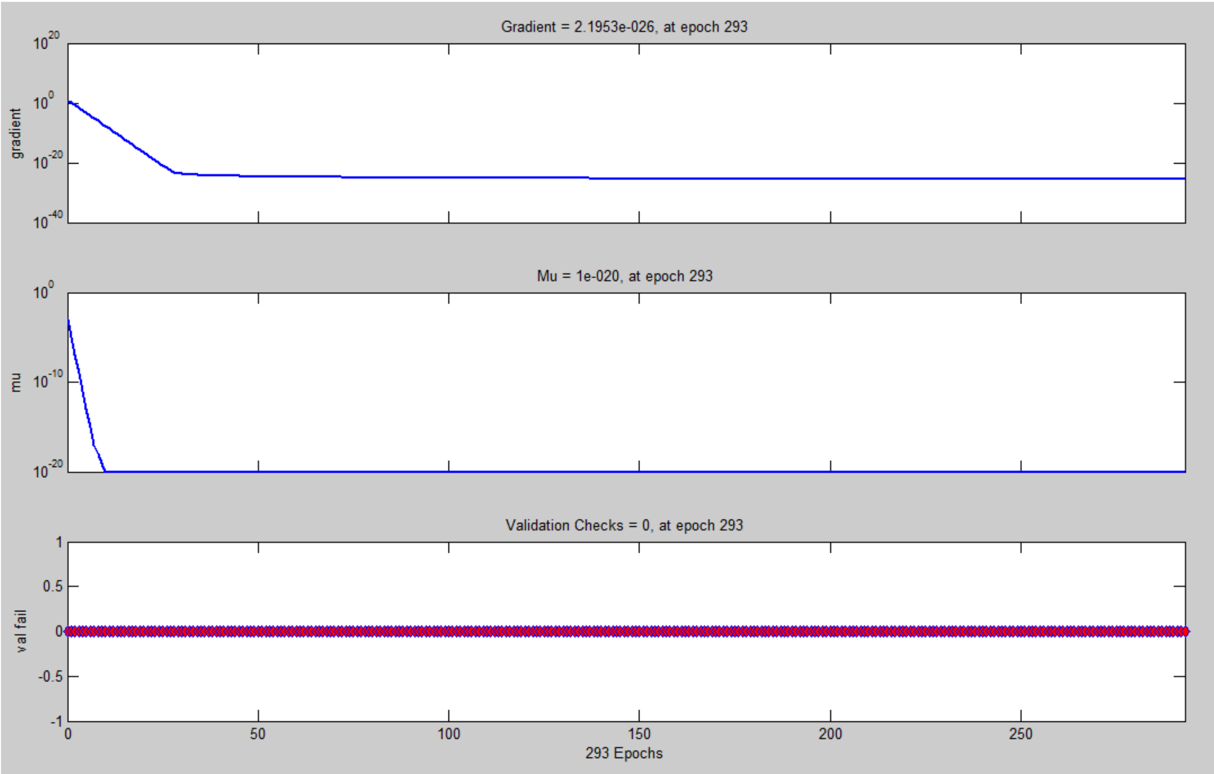


Fig 4.5: training state parameters during the training of the network

Note: the weights obtained from the above network are utilized for implementation in SIMULINK model for real-time implementation.

Note: the accuracy during the training of the network was found to be 99.5%. (Only 1 out of the 200 samples tested returned a negative result). The recognition accuracy can be increased by training the above neural network with a very large number of samples.

SIMULINK MODEL IMPLEMENTATION

The offline analysis was followed by the implementation of the results so obtained in a SIMULINK model for simulation of a real-time implementation of the model. The different parts of the model are described below.

Basically the system structure is same as described in the first chapter. However the final SIMULINK structure looks like the figure given below. The additional blocks are due to the different input and output compatibility of the blocks in SIMULINK. For example, the DWT block takes in a frame based input of frame size of two elements and the input blocks outputs a frame size of one. Therefore, a buffer block is needed to convert the frame size from one to two.

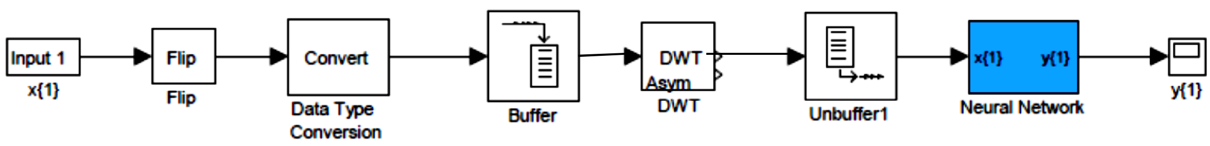


Fig : SIMULINK diagram for the whole structure

The individual blocks and their usage are described below.

(i) **Input block:** This block holds the input values of the signal, which is passed on to the preprocessing blocks for wavelet decomposition. The frame size of the signal is one, which is incompatible with the DWT block, which takes in an input of frame rate 2. Thus, some other blocks are added to the network in between those blocks.

(ii) **Matrix flip block:** the function of this block is to flip the matrix input from input block to form a column matrix. This makes the input format of the buffer compatible with the input block.

(iii) **Data type conversion:** converts the data format for compatibility.

(iv) **Buffer:** buffer adjusts the frame rate so that the frame rate is same as that required by the DWT block.

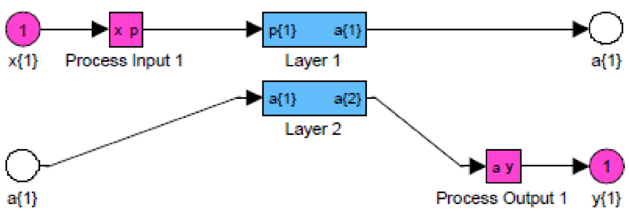
(v) **DWT block:** This part does the actual processing in the preprocessing part of the model. As in the offline analysis, the DWT block decomposes the signal into approximation and detail parts using the Daubechies wavelet of order 2, and in the process reduces the number of samples to one fourth of the original. This makes processing at the neural network part lot simpler.

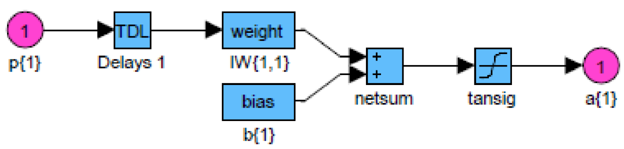
(vi) **Unbuffer:** This block has the same functionality as the buffer block; the only difference being the frame size is converted from two to one, which makes it compatible with the neural network block.

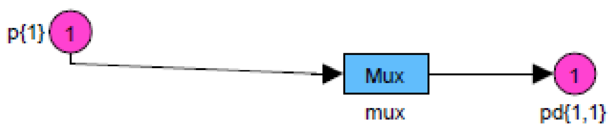
(vii) **Neural network block:** the neural network block recognizes the type of arrhythmia, thus diagnosing the disease.

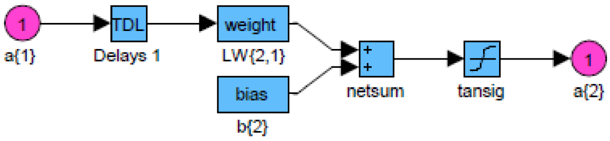
(viii) **Scope:** used for visualization of the output.

Some other figures that form a part of the SIMULINK implementation are shown below.





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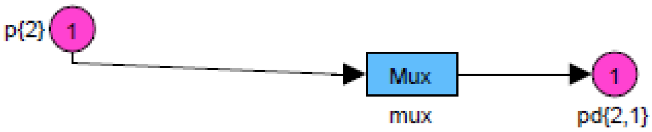
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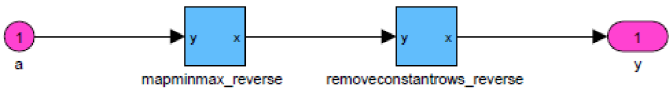
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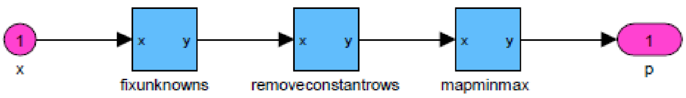
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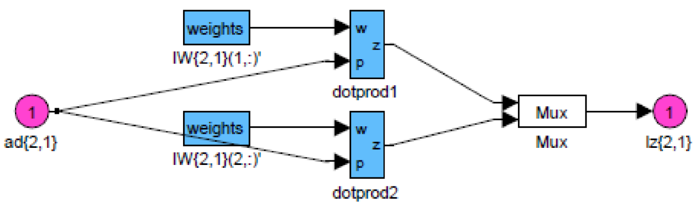
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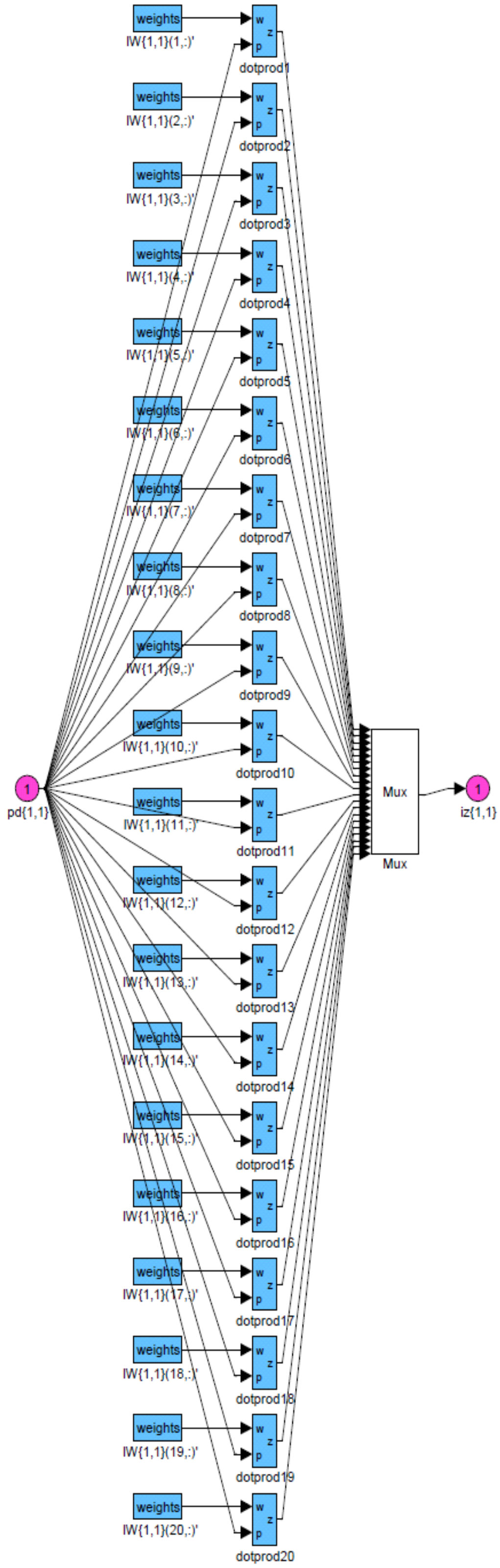
1
lz{2,1}


weights
IW{1,1}(1,:)'
dotprod1
dotprod2
dotprod3
dotprod4
dotprod5
dotprod6
dotprod7
dotprod8
dotprod9
dotprod10
dotprod11
dotprod12
dotprod13
dotprod14
dotprod15
dotprod16
dotprod17
dotprod18
dotprod19
IW{1,1}(20,:)'
dotprod20
1
pd{1,1}
Mux
Mux
1
iz{1,1}

Simulink results

The results of simulation are shown below. The simulation is done with the help of a synthesized input signal. The topmost figure is the source signal and the subsequent are normal sinus atrial fibrillation and supraventricular arrhythmia respectively.

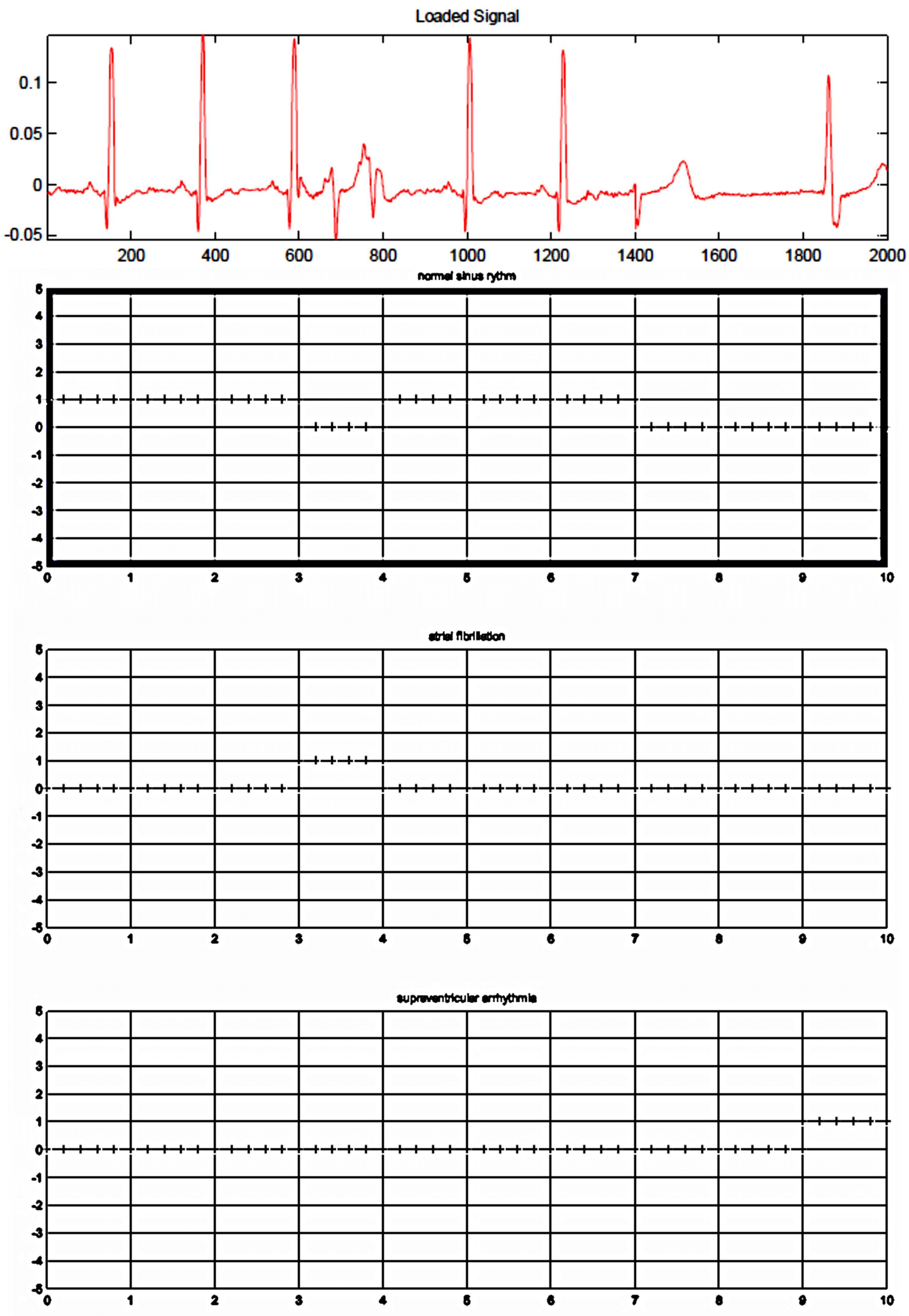


fig 5.2 SIMULINK simulation result

CONCLUSION AND FUTURE WORK

Realtime ECG processing holds a great potential for development. Automated arrhythmia detection could not only help in early detection of diseases but also in reducing the workload of the medical data analyst. The aim of Discrete Wavelet Transform is to reduce the number of samples and eventually reducing the complexity of the neural network and the computation time of the neural network.

However, modern technology has made intensive processing highly feasible and economical. Computing platforms such as FPGA, PLD, DSP and microprocessors can be used for interfacing the model with the actual Holter Device.

Of all devices mentioned above FPGA is the most promising because of its speed and flexibility. FPGA platforms provide great support for many types of interfacing standards and are hence recommended for implementation in a realtime scenario. Microprocessors, though not as fast as the FPGA platform also holds great promise as they are relatively in expensive and are easier to program.

The algorithms given here utilise data from 19 subjects. Training the model with a large number of test data would greatly enhance the accuracy and hence the reliability of the system.

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